REPORT

SUSTAINABILITY

CFA Institute Research & Policy Center

Modeling Climate Transition Risk: A Network Approach

Raymond Pang and Gireesh Shrimali

Executive Summary

Climate transition risks represent a severe threat to financial stability. By climate transition risks, we mean those "risks related to the transition to a lower-carbon economy."[1] They can arise from policy implementations, technological advancements, or market behavior shifts (or some combination of these factors). For example, a climate transition scenario wherein climate-related policies target warming of 1.5 degrees Celsius above preindustrial levels instead of 2 degrees Celsius can lead to a higher markdown in the value of fossil fuel–exposed assets held by financial firms. Therefore, investors should understand the nature of climate transition risks, their exposure to these risks in investment and loan portfolios, and the systemic implications of climate transition risk in an interconnected financial system with multiple layers of counterparty exposures.

Various institutions, such as banks and insurance firms, consider climate transition risks when determining risk premiums or aligning their loan books and operations with sustainability targets. Identifying climate transition risks is also important for policymakers: Central banks and regulatory authorities should account for transition risks and their implications for financial stability to inform future policymaking and supervision.

One way to assess climate transition risks is through a scenario-based approach. Rather than measuring transition risks only from market movements observed in historical data, we can incorporate changes in firms' expected future returns into present valuations of physical and financial assets using forward-based transition scenarios. We use a scenario methodology because evidence suggests that financial markets have not fully incorporated transition risks into asset valuations and projected corporate performances (Bolton, Despres, Pereira da Silva, Samama, and Svartzman 2020). Additionally, few historical

[1]See www.epa.gov/climateleadership/climate-risks-and-opportunities-defined.

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events represent the expected losses financial firms face from climate transition risks. Therefore, scenarios motivated by different climate transition narratives and physical climate targets can reflect the landscape of potential losses.

Using a case study of developing countries in Asia, a region with prevalent climate transition risks, we model the cascade of losses between financial firms under different transition scenarios. We adopt a systems-thinking approach, recognizing that transition risks are not confined but extensively interact within an interconnected financial system. By analyzing the cumulative increase in losses in the system, we can measure the scale of higher-order losses and their associated pathways.

While climate transition risk can be transmitted through different channels, we focus on the dynamics of transition risk across three layers: the specific scenario itself, the overall economy, and general financial considerations, whereby financial firms facilitate loans to energy firms and borrow and lend to one another (through interbank and short-term lending). Each layer conceptually describes a way to compartmentalize key parts of the system used to model the transmission of losses. The financial layer includes two types of firms: energy firms, which are directly affected by the transition scenario (based on the Network for Greening the Financial System scenarios), and financial firms, which are indirectly affected by the loans they provide to energy firms. The three layers are defined as follows:

- **Scenario:** This layer represents transition risk scenarios associated with energy firms' physical assets, such as coal, oil, and gas. Losses in energy firms' physical assets are translated into economic scenarios affecting the firm's future revenues, which depend on the energy firm's projected production and the price of physical assets under a business-as-usual scenario compared with the realized transition scenario.
- **Economy:** The differential in the trajectory of energy firms' revenue from physical assets across future years is accounted for under a discounted cash flow model. The change in revenue under the discounted cash flow model reduces the net present value of the physical asset, decreasing profits and the book value of equity.

- **Financial**

  Energy to Financial: Losses from the energy firm under the transition scenario are incurred by financial firms that provide loans to energy firms. Financial firms incur losses through a mechanism of credit valuation adjustments (CVAs), which account for the decrease in the energy firms' creditworthiness under the transition scenario. Such adjustments by the financial firm factor into the energy firms' reduced ability to meet their obligations, leading to a decrease in the initial value of the loan held as an asset by the financial firm. The markdown in the financial firm's counterparty asset decreases its total assets and book value equity.

  Financial to Financial: Losses from the financial firm affected by the loans provided to energy firms spread to other financial institutions that hold counterparty asset holdings of the affected firm. There is a decrease in equity of the financial firm holding the counterparty asset from the affected financial firm through CVAs, similar to the impact of loans from energy firms under the transition scenario. This triggers losses to other financial firms, where multiple CVAs occur, accounting for a decrease in the firms' creditworthiness and leading to a contagion of losses in the financial system.

This framework is advantageous in capturing the granularity of energy firms' physical asset holdings toward the complexity of contagion in financial firms.

We include a sensitivity analysis to explore the uncertainty in losses from the climate transition scenario and financial network. The uncertainty in the transition scenario is due to the assumptions in projecting future transition risk. For example, including carbon prices in some scenarios can vary firms' losses in fossil fuel–based asset holdings. Differing assumptions give rise to multiple transition scenarios, where all scenarios can be argued to be plausible. Additionally, uncertainty exists in the financial network, because we do not fully observe the financial dependencies between firms. From the network, multiple configurations that are structurally different from one another, yet consistent with the data, can change the magnitude of financial firms' total losses, leading to varying conclusions on the impact of transition risk. As a result, we characterize a range of losses to inform how the uncertainty of the scenario and network manifests in the financial system.

We present the following results and recommendations:

- **Average equity losses for financial firms in smaller economies are comparable to those for firms in larger economies.** They are comparable because of the exposure of financial firms in smaller economies to financial firms in larger economies, where there is a spillover in losses. Our case study of developing countries in Asia shows that the average expected equity losses to financial firms in China—representing the largest market in asset holdings—are around $11 million. In comparison, financial firms in Thailand and Vietnam, which have smaller total asset holdings, incur average equity losses of around $6 million. The difference is small relative to the total book value equity for financial firms in each market, which for Chinese financial firms is almost 70 times higher than for firms in Thailand and 135 times higher than for firms in Vietnam. Overall, the difference in financial firms' book value of equity far exceeds the difference in losses among firms.

- **Across all financial firms, contagion losses from the financial network (driven mainly by Chinese financial firms) contribute more than 40% to equity losses,** a high figure considering that financial counterparty asset holdings comprise only 4.5% of financial firms' total asset holdings. This result is significant because, under reasonable assumptions, it shows that losses between financial firms can be larger than the direct losses under the transition scenario. These higher-order losses arise only when using a network methodology and would not be identified by considering financial firms' balance sheets in isolation.

    Recommendation: Given that today's capital markets are both global and interconnected, regulators should consider financial firms' transition risk exposures in their jurisdiction. This can be achieved by understanding network contagion and the sources and magnitude of potential losses arising from transition risk exposures in third countries.

- **The range of financial firms' equity losses decreases for financial networks wherein the interdependencies between firms are high.** We consider a range of equity losses because different networks can be generated at lower network densities.[2] An increase in the number of links between financial firms leads to a decrease in the quantity of counterparty assets that any firm holds of another firm. Depending on the network, the network density can either decrease or increase contagion losses in the financial network if firms holding these counterparty assets are resilient or vulnerable to shocks. Results from our case study show a small deviation in equity losses under different networks, where the range of equity losses is high at lower densities, particularly at 10%, and then decreases as the network density increases in the financial network. Changes in the network density have a contrasting impact on equity losses under transition scenarios. Such ranges should be factored into a firm's risk management metrics to account for the uncertainty that arises from not fully observing the network.

    Recommendation: Individual firms can mitigate losses from a risk management standpoint by increasing capital buffers. From the network perspective, firms should account for the risks that could arise in each counterparty asset class, particularly in networks with a lower network density.

[2]The network density is the number of links between financial firms relative to the total number of links that could be established in the financial network.

Introduction

Climate transition risks present large, imminent threats to the financial system. In 2015, Mark Carney, then-governor of the Bank of England, described climate change as the "tragedy of the horizon," and he underlined the threats that climate transition risks pose to financial stability (Carney 2015). Almost a decade later, policymakers and regulators have shifted from regarding climate transition risk as a future concern to a clear and present danger. Indeed, in 2023 Frank Elderson, an executive board member of the European Central Bank, noted this shift: "Back in 2015[,] Mark Carney spoke about the tragedy of the horizon. Eight years on, we have arrived at that horizon. The tragedy is upon us[,] and it has started to unfold" (Elderson 2023). According to the International Energy Agency and the International Finance Corporation, climate mitigation investments of approximately $2 trillion a year will be required in emerging markets and developing economies by 2030 (IEA and IFC 2023). The materialization of climate transition risks means that we need methodologies to evaluate firms' climate risk exposures.

Transition risks in the financial system can be accounted for using systems thinking and network methodologies. A network represents firms' interdependencies in the system, where losses propagate through financial firms' asset holdings based on mark-to-market adjustments. We can see these network dynamics in play with the case of the 2008 global financial crisis (GFC), which originated from the US subprime mortgage market collapse. Losses from defaulted large and interconnected firms, such as Lehman Brothers, spread to other firms through the interbank market, credit default swaps, and deposit withdrawals. The risks of default from other counterparties and asset markdowns undermined confidence in the credit market, making firms more vulnerable to subsequent market shocks. These impacts in the United States affected countries in Europe and Asia, representing a systemic event for the financial system—with an estimated loss of trillions of dollars to the global economy. Similarly, Haldane and May (2011) draw analogies with the dynamics of a biological ecosystem and the networks involved in an epidemic event to understand the GFC. By accounting for the collective impact of financial firms, we can model the interactions between the climate and the financial system.

In this paper, we use a general network reevaluation model to consider financial contagion under climate transition risk. We present a model to assess the losses that can arise for financial firms that are exposed to firms in the real economy, represented in this case by energy firms. The model's generality means that different valuation frameworks (the process by which firms account for the mark-to-market evaluation of assets based on their counterparties' creditworthiness) and contagion channels can be included. We use a case study of developing countries in Asia to illustrate this model, examining expected loss sensitives that arise from the valuation framework, network topology, and climate transition scenario. Because there is uncertainty in the transition scenario and the formation of the financial network from the unobserved data, depending on the scenario and methodology used, this can lead to a high deviation in losses among financial firms, which should be accounted for when assessing climate transition risks.

We use the Network for Greening the Financial System (NGFS) scenarios to model the direct impact of transition risk. NGFS scenarios are intended to assess the macrofinancial risks institutions face under climate change. Each scenario is a trajectory of impacts that climate-related policies and regulations might have on physical assets. For example, a scenario in which policies that accelerate the green transition are introduced early can rapidly decrease the production of fossil fuels and increase investment in renewable energies. Such developments have implications for a financial firm's portfolio: Investments in renewable energies could benefit from the uptake of green assets, whereas a high carbon exposure portfolio would be negatively affected. Crucially, these scenarios are not forecasts, but a set of plausible scenarios that institutions can use to assess transition risks.

We review seven transition scenarios provided by NGFS, including the Current Policies scenario (the business-as-usual, or BAU, scenario, with 2.9-degrees Celsius end-of-century warming) and the Net Zero 2050 scenario (NetZero, with 1.4-degrees Celsius end-of-century warming). We also include the Below 2°C scenario (Bel2, with 1.7-degrees Celsius end-of-century warming), the Delayed Transition scenario (Del, with 1.7-degrees Celsius end-of-century warming), the Fragmented World scenario (Frag, with 2.3-degrees Celsius end-of-century warming), the Low Demand scenario (Low, with 1.4-degrees Celsius end-of-century warming), and the Nationally Determined Contributions scenario (NDCs, with 2.4-degrees Celsius end-of-century warming).[3]

Transition scenarios consider a range of impacts based on changes in market behavior, policy, or technological advancements by using an integrated assessment model (IAM) with detailed climate information and economic and financial variables. As stated in a UN Sustainable Development Solutions Network (SDSN) Global Climate Hub report, IAMs "aim to provide policy-relevant insights into global environmental change and sustainable development issues by providing a quantitative description of key processes in the human and earth systems and their interactions" (Koundouri, Chatzigiannakou, Dellis, Landis, Papayiannis, and Yannakopoulos 2024).[4]

We use NGFS scenarios under the downscaled global change analysis model, where further macroeconomic forecasts are generated under NiGEM, a high-dimensional variable econometric model built by the National Institute of Economic and Social Research (NIESR).[5] In "NGFS Climate Scenarios Technical

[3]See NGFS (2023) for further detail on the seven transition scenarios. The temperatures per the NGFS scenarios are subject to periodic updates and may differ from the temperatures used in this analysis, which were taken as of the time this research was conducted.

[4]For access to the full report, visit https://unsdsn.globalclimatehub.org/un-sdsn-global-climate-hub-report-modelling-net-zero-pathways/.

[5]Information on NIESR is provided at https://www.niesr.ac.uk/.

Documentation, V4.2," these scenarios are categorized into four groups (NGFS 2023):

- **Orderly transition (including NetZero, Low, and Bel2):** scenarios in which climate policies are introduced early and become stricter toward the end of the time horizon
- **Disorderly transition (including Del):** scenarios with a higher transition risk because policies are introduced only in later stages and are divergent (differences in the speed and direction of country-implemented climate policies)
- **Hot house world (including NDCs and BAU):** scenarios that assume the introduction of some climate policies but not to the level needed to prevent catastrophic damages from climate change
- **Too little, too late (including Frag):** scenarios that assume that policies are implemented too late to prevent physical risks

Although we focus our analysis on the NetZero scenario, we examine losses from all transition scenarios as part of a wider sensitivity analysis.

Literature Review

Our study adds to the existing academic literature on evaluating climate transition risks for financial firms. In general, the literature does not extensively investigate the combination of underlying inputs used to assess financial firms' exposure to transition risks (e.g., the assumed transition scenarios firms are exposed to, the time at which the transition scenarios occur, or the network topology measuring the interconnectedness of financial firms through their counterparty asset holdings). Considering only a single input for each does not account for the range of assumptions or directions in the literature. Our study provides a wider sensitivity analysis to measure the uncertainty assumed in modeling transition risk.

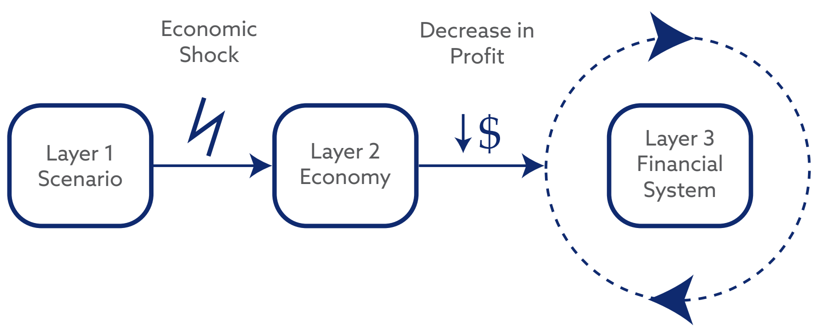
Previous research in evaluating credit and market risks under transition scenarios is considered in works by Nguyen, Diaz-Rainey, Kuruppuarachchi, McCarten, and Tan (2023), where they provide a modified credit-risk model to estimate losses for US-syndicated loans across fossil fuel energy firms. Battiston, Mandel, Monasterolo, and Roncoroni (2023) adopt a credit-risk methodology, deriving a closed-form probability of default (PD) expression for firms that accounts for a firm's capital structure, energy technology profile, and market expectations of climate scenarios. Approaching climate risk from a market-based standpoint, Jung, Engle, and Berner (2021) develop the "climate beta" concept to measure climate risk factors in stock returns. Contrary to Jung, Engle, and Berner (2021), we do not assume that climate risks are fully factored into the financial markets. Evidence suggests that firms do not fully account for transition risks, as stated by Bolton, Despres, Pereira da Silva, Samama, and Svartzman (2020). If financial firms underestimate the potential scale of transition risks, they are likely to see significant losses in their portfolios.

There has been active research evaluating transition risks to the financial sector from academia and industry. Nonacademic climate stress testing models, such as agent-based modeling employed by Cormack, Donovan, Koberle, and Ostrovnaya (2020), apply macroeconomic factors to a case study of European utility firms. In 2018, the think tank 2° Investing Initiative (2DII) introduced the Paris Agreement Capital Transition Assessment (PACTA), an open-source methodology tool that evaluates the climate impact on financial firms' portfolio companies based on five-year production plans.[6] We believe that the network approaches used in our study capture financial-level contagion effects that could enhance the methodologies and tools that PACTA presents, which benefit from high-quality data and individually defined firm behaviors.

Model

We quantify losses to energy firms using the TRISK model (Baer, Caldecott, Kastl, Kleinnijenhuis, and Ranger 2022). Baer et al.'s climate stress test "translates climate transition risks affecting individual firms and economies to shocks affecting the financial system" using the forward-looking risk measure TRISK, or transition risk. TRISK "is the expected loss of a financial institution given the uncertain materialisation of a transition stress scenario" (Baer et al. 2022). We assume that the network comprises energy and financial firms. **Exhibit 1** shows the extended TRISK flow diagram used in this paper: Energy firms hold physical assets, meaning that a climate-transition scenario (layer 1) affects the revenues that energy firms' physical assets generate, in turn reflecting an economic scenario for firms. Changes in revenue represent projections over a given scenario time horizon using a discounted cash flow

Exhibit 1. Extended TRISK Flow Diagram



Notes: This is a flow diagram of the TRISK model, accounting for energy firms' direct losses under the transition scenario across three layers: scenario, economy, and financial system. We extend the modeling in layer 3, accounting for the spillover losses between financial firms (represented by the dotted circle).

[6]See RMI (2022) for more information on 2DII, PACTA, and the transfer of PACTA's stewardship from 2DII to RMI.

(DCF) model. Changes in DCFs lead to a loss in asset net present value, a reduction in firm profitability, and losses to the book value of equity (layer 2).[7]

In layer 3, we extend TRISK by using a general reevaluation model as introduced by Barucca, Bardoscia, Caccioli, D'Errico, Visentin, Caldarelli, and Battiston (2020). We measure financial firms' losses from exposure to energy firms via the loans (energy assets) the financial firms provide. From CVAs that financial firms perform, there is a markdown on the energy assets financial firms hold to account for the energy firm's decreased creditworthiness under the transition scenario. As a result, CVAs translate to losses in the book value of equity of the financial firm. These losses then spread to other financial firms from CVAs performed by counterparties relating to interbank assets (bank-to-bank lending of long maturities), short-term assets (lending across all financial firms of short maturities), and other counterparty assets. The decrease in the creditworthiness of other financial firms leads to further losses, where continuous iterations occur through multiple counterparty asset holdings until a fixed point is reached.[8] We quantify losses by the change in asset holdings, equity, and associated PD. An example illustrating the reevaluation model is provided in the appendix.

Data

Energy Firms

We use data from LSEG (formerly Refinitiv) and focus our analysis on a case study of coal production mining firms in Australia and Indonesia. We consider coal production mining firms (as opposed to the broader set of fossil fuel energy firms) that have been directly affected by the transition scenario. Firms in these countries are particularly exposed to transition risks because of the large volume of coal exports they provide to developing countries in Asia. For context, Indonesia and Australia represent the largest and second-largest coal export countries in 2020, respectively, indicating a large source of transition risks for exposed financial firms in Asia and globally.[9]

Financial dependencies arise through loans provided by financial firms in this region. Losses to coal producers under the transition scenarios can generate spillover effects on the financial system in the broader Southeast Asia region. In 2022, coal contributed to 41% of total global fossil CO2 emissions—a 1.6% increase from 2021 (Global Carbon Project 2023). The International Monetary Fund identifies challenges to climate goals for emerging markets and developing economies because of these countries' high dependency on coal (IMF 2023). Therefore, the losses from this physical asset are representative of a sizable

[7]The discount rate firms use to discount cash flows from energy assets is calculated using the capital asset pricing model (CAPM). Further detail can be found in the academic version of this paper (Pang and Shrimali 2024).

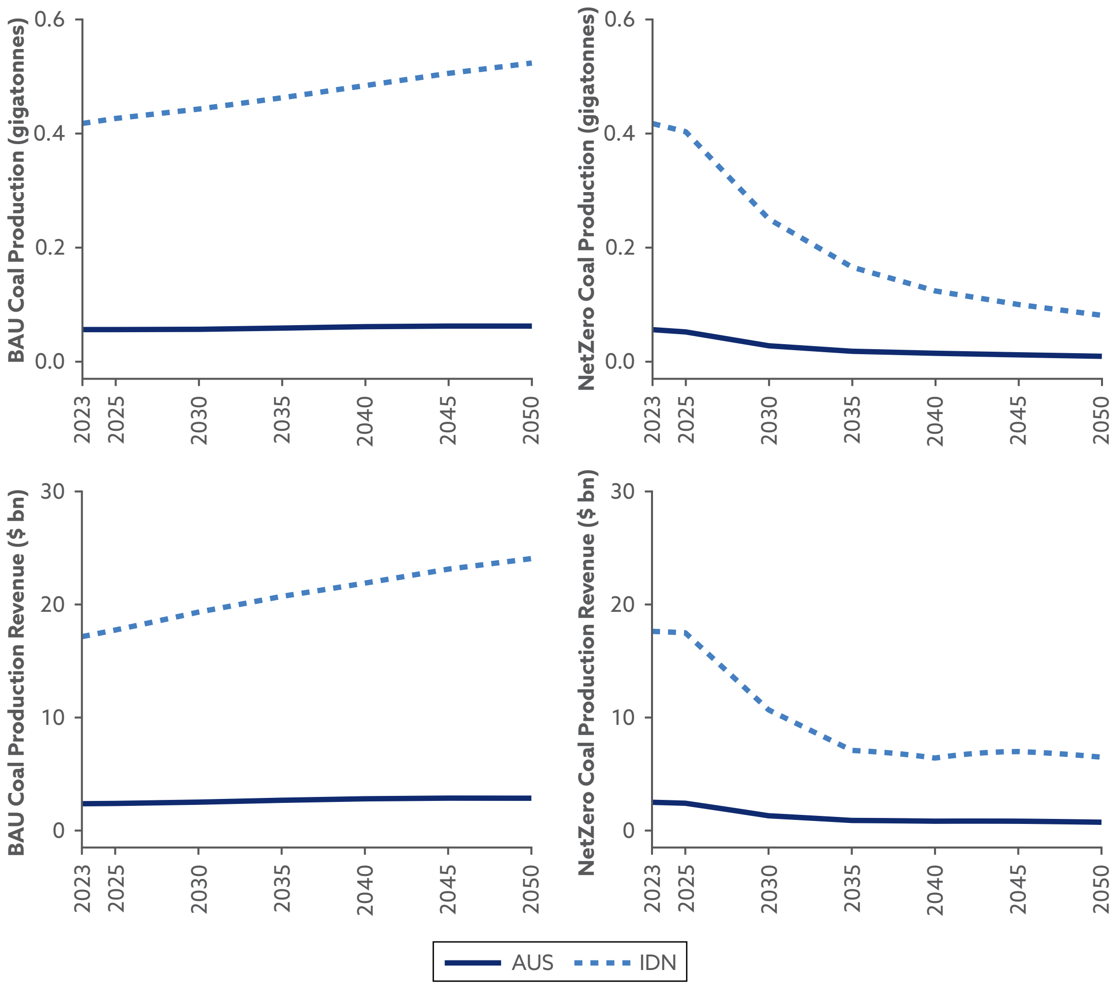
[8]The fixed point represents an equilibrium position where firms have adjusted to all changes under the transition scenario.

[9]See Our World in Data: https://ourworldindata.org/explorers/natural-resources.

proportion of climate risks that developing countries in Asia face. Our focus on coal production mining firms is an illustrative case study examining key network sensitivities. Including other energy firms and sectors would develop this methodology into a comprehensive climate stress test approach.

Comparing the volume of coal production under the BAU and NetZero scenarios (see **Exhibit 2**), we find that Indonesia's coal production exports[10] are higher as of 2023 than Australia's, at 0.4 gigatonnes versus 0.06 gigatonnes, respectively.

Exhibit 2. Coal Production and Revenue under BAU and NetZero Scenarios for Australia and Indonesia



Notes: The exhibit presents the volume of coal production exports (top row) and revenues (in $ bn) from coal production exports (bottom row) for firms in Australia (AUS) and Indonesia (IDN) under the BAU (left column) and NetZero (right column) climate transition scenarios. Scenario times are defined between 2023 and 2050.

Source: NGFS scenarios (2023).

[10]We assume total coal production equates to total coal exports for simplicity.

The higher volume of coal production exports reflects the higher number of firms in Indonesia than in Australia—27 compared with 16—and the relatively large volume of exports from Indonesia to China and other countries, such as Japan and South Korea.

Under the BAU transition scenario, Exhibit 2 shows that Indonesia's coal production exports continue to increase, reflecting the increased demand in countries such as the Philippines and Thailand. The trend is different under the NetZero scenario, wherein Indonesia's coal production decreases from 2023, with the steepest reductions occurring in the first 10 years of the scenario period. The reduced volume of Indonesia's coal exports is driven by the decreased demand for coal in China, which is a large importer of Indonesian coal. Australia's coal exports are relatively smaller than Indonesia's exports, leading to a flatline of coal exports under the BAU and NetZero scenarios.[11] The trends between the BAU and NetZero scenarios would still lead to a decrease in the demand for coal by Australian coal exporters.

For coal production revenue, represented by the bottom row in Exhibit 2, we find a similar trajectory in Indonesia that follows coal production volumes. Under the BAU scenario, revenues track production volumes because coal prices are assumed to remain unchanged across all years. Under the NetZero scenario, coal prices decrease until 2035, then increase in 2050. This is reflected in Indonesia's coal revenue, which shows a small increase between 2035 and 2045. Overall, we find the largest driver of revenue changes is the reduction of coal production volumes from 2023.

We next consider the economic impacts on energy firms represented by layer 2 in the model, including the expected changes in revenues under the DCF model, and on each firm's book value of equity. **Exhibit 3** shows that the mean firm risk premium is higher in Indonesia than in Australia and is reflected across the mean firm beta, risk-free rate, and market risk premium components.[12]

Under the DCF model, a higher firm risk premium will lead to a higher exponential discounting of cash flows, decreasing Indonesia's profits relatively more than Australia's profits.[13] The aggregated balance sheet shows that Indonesian firms have higher book value equity than Australian firms. Although the balance sheet shows that Indonesia has higher total asset and equity holdings, if we account for liability holdings under the capital ratio, we find that Indonesia's mean capital ratio is lower than Australia's.[14]

[11]Because some coal production firms in Australia are not included, export volumes are underestimated. This is due to a lack of data; if we were to account for a wider range of Australian coal exporters, we would expect these values to be higher.

[12]For reference, under the CAPM, Firm risk premium = Risk-free rate + Firm beta × Market risk premium. The mean values are based on the firms' designated country.

[13]An energy firm's profits in physical assets are calculated by multiplying the volume of production in the physical asset, the price of the physical asset, and the firm's profit margin in the physical asset. We assume that the profit margin for energy firms' coal exports is 15%, given that we do not have data on energy firms' costs.

[14]The capital ratio is a firm's book value equity relative to its total liabilities.

Exhibit 3. Aggregated Balance Sheet Data for Energy Firms by Market

Market	Mean Firm Risk Premium	Mean Firm Beta	Risk-Free Rate	Market Risk Premium
AUS	7.50%	0.83	4.4%	3.7%
IDN	11.69%	1.03	4.8%	6.7%
Number of Firms	**Total Assets (in $ bn)**	**Total Liabilities (in $ bn)**	**Total Equity (in $ bn)**	**Mean Capital Ratio**
16	20.01	7.59	12.42	13.60
27	54.10	24.04	30.06	2.55

Note: The exhibit presents the economic data used in the DCF model and aggregated balance sheet data for energy firms, denoted by market (the first row is for Australia, and the second row is for Indonesia).

Source: LSEG.

For our results, we assume that the reevaluation of firm counterparty assets occurs based on the capital ratio of the counterparty, which is triggered by the decrease in counterparty equity. For the reevaluation process, decreasing the capital ratio increases the markdown of assets of the associated counterparty and subsequently lowers its book value equity, leading to a chain of losses.[15]

The data in Exhibit 3 indicate that financial firms will face larger losses on Indonesian counterparty assets (loans) than Australian counterparty assets. This is because of the greater revenue losses in Indonesia than in Australia under the DCF model and transition scenario, the lower capital ratio of Indonesian firms, and the higher number of firms in Indonesia, which, taken together, amplify losses for financial firms.

Financial Firms

In layer 3, we include data from LSEG on financial institutions from East, South, and Southeast Asia. We consider financial institutions in China (mainland), Indonesia, India, Malaysia, Philippines, Thailand, and Vietnam. These countries represent some of the world's largest economies and populations. The negative impacts of transition risks to these countries will significantly affect Asia and other regions. In a regional report, the IEA discussed the vulnerability of Southeast Asian countries, particularly Thailand and Vietnam, as a result of their existing energy use and energy impacts from geopolitical events, such as the Russia–Ukraine war (IEA 2022).

[15]We use the valuation framework by Veraart (2020), which incorporates the capital ratio into a beta distribution. This distribution can be adjusted to account for climate risks not reflected in normal or uniform distributions. We consider a wider range of valuation frameworks as part of an extended sensitivity analysis in the academic version of this report (Pang and Shrimali 2024).

Next, we describe financial firms' aggregated balance sheets by market in **Exhibit 4**. We include the number of financial firms: banks, investment banks, and investment management firms. We also include financial firms' counterparty asset holdings, representing the contagion channels through which losses propagate. We assume that banks hold counterparty assets in all asset classes, whereas investment banks and investment management firms can hold only short-term assets. The assumptions on the data reflect the differences in the balance sheets of different financial firms.

The data in Exhibit 4 show that Chinese financial firms have the highest total assets and equity. Total counterparty assets for Chinese financial firms are 10 times higher than for Indian firms, which have the second highest asset holdings. The volume of assets for Chinese financial firms comes from the number of institutions in the data and the size of the financial firms. Firms' interbank asset holdings are higher than their short-term assets in all markets except the Philippines, indicating that interbank assets will contribute a relatively sizable proportion of expected losses. The mean capital ratios for financial firms (calculated in the same way as for energy firms) are smaller than for energy firms because of the higher volume of liabilities financial firms hold. The mean capital ratio is smallest for financial firms in Malaysia at 0.51, followed by China at 0.67 and Vietnam at 1.34. While the total equity of financial firms in China is high, if we account for both the quantity of counterparty asset holdings

Exhibit 4. Aggregated Balance Sheet Data for Financial Firms by Market

	Number of Firms			Total Assets ($ bn)				Total Liabilities ($ bn)	Total Equity ($ bn)	Mean Capital Ratio
Market	Banks	IB	IM	External	Energy	Interbank	Short-Term	External		
CHN	442	88	327	59,116.79	25.47	1,744.87	969.27	52,444.18	6,698.08	0.67
IDN	72	7	2	876.50	0.40	39.67	6.27	738.03	138.87	5.47
IND	156	198	116	4,203.53	1.67	152.89	31.00	3,853.61	351.60	4.70
MYS	43	4	3	1,383.05	0.46	43.08	21.08	1,219.27	164.23	0.51
PHL	20	2	2	478.72	0.21	13.06	17.25	429.53	49.40	2.07
THA	13	13	1	766.14	0.45	34.79	2.06	669.21	97.38	2.90
VUT	28	20	2	461.14	0.58	61.03	35.40	412.49	49.23	1.34

Notes: The exhibit shows the number of banks, investment banks (IB), and investment management (IM) firms in each market: China (CHN), Indonesia (IDN), India (IND), Malaysia (MYS), Philippines (PHL), Thailand (THA), and Vietnam (VUT). Additionally, for each market, the aggregated balance sheet for assets, liabilities, and equity ($ bn) is displayed, where asset holdings comprise external assets (indicating non-counterparty assets) and counterparty assets in energy firms, interbank, and short-term assets. Because firms' counterparty liabilities are not displayed, we assume that firms hold equal quantities of counterparty assets and liabilities.

Source: LSEG.

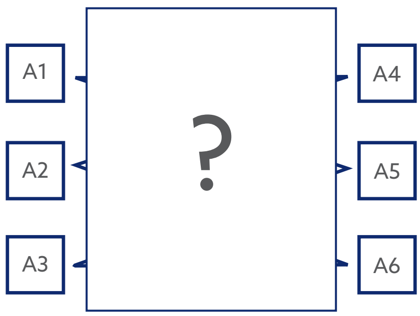
that Chinese financial firms hold and the lower capital ratio associated with Chinese financial firms, Chinese firms could be a large source of contagion.

We use matrix reconstruction methods to account for the uncertainty in the financial network. Matrix reconstruction methods form a structure that represents a network in which only partial information is used. In our case, the partial information is knowing the total counterparty assets and counterparty liabilities financial firms hold but not observing the individual links between firms (as illustrated in **Exhibit 5**). As a matrix, this is equivalent to knowing the row and column sums but not knowing the individual matrix entries. Given that an infinite number of networks could be inferred by observing only the partial information, we use matrix reconstruction methods in which specific network features are embedded. Our analysis will first use the entropy method (Upper 2011) and then the statistical physics method, denoted as StatPhys (Cimini, Squartini, Garlaschelli, and Gabriella 2015) in the sensitivity analysis.[16] We use these methods for their computational speed and the StatPhys for its ability to calibrate networks to a given network density.[17]

Results

Result 1: Under the NetZero transition scenario, financial firms' losses are highest in large economies where these losses spill over to smaller economies. We plot the projected equity losses for energy firms under the NetZero scenario in **Exhibit 6**, representing the direct equity losses under the transition scenario. We assume that the direct equity losses to energy firms under the DCF model are based on a time horizon of projected revenues between 2023 and 2050 and then aggregated.

Exhibit 5. Partial Information in Financial Networks

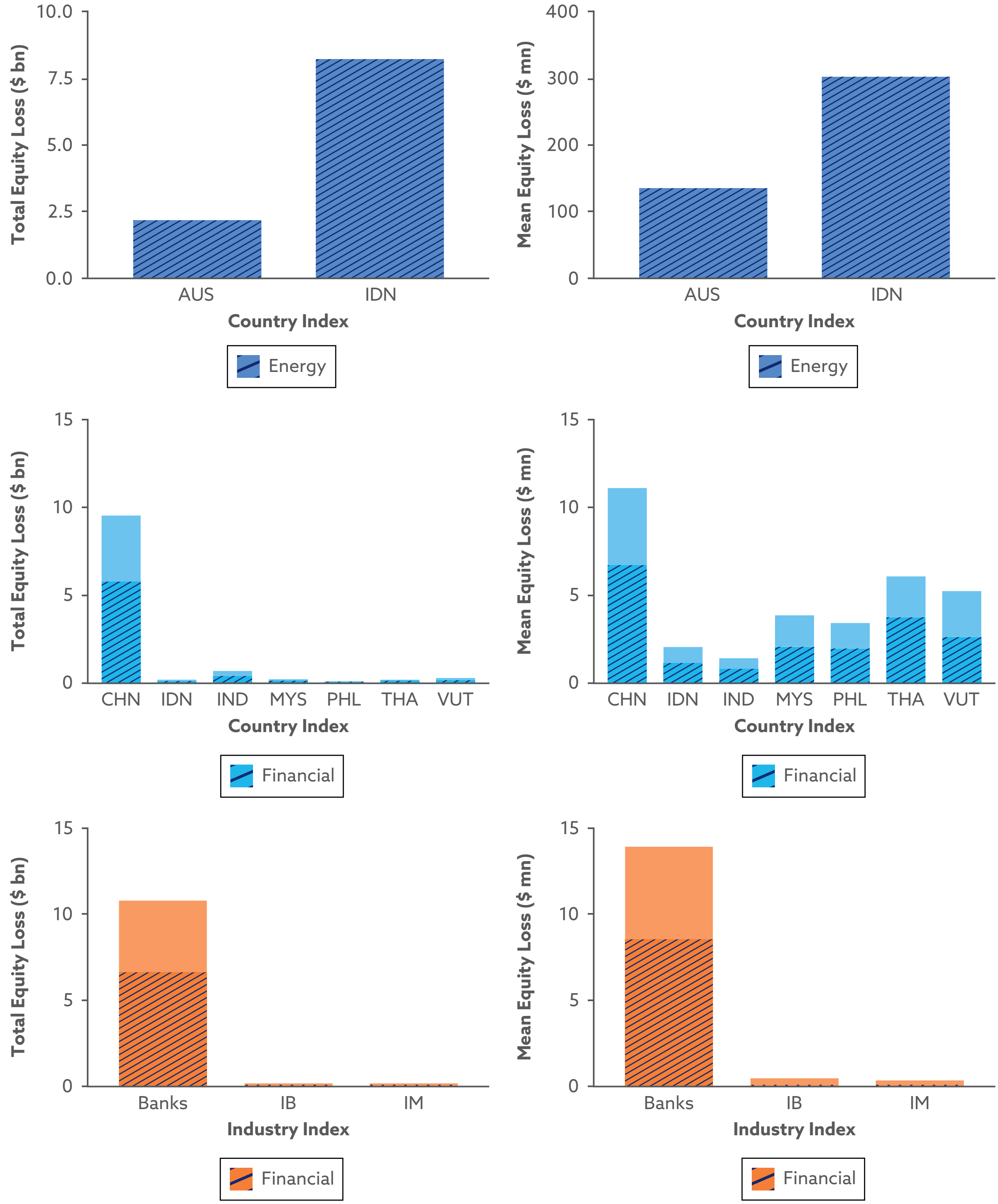


Notes: This exhibit represents the data uncertainty that requires the use of matrix reconstruction methods. While the total counterparty assets and counterparty liabilities firms hold (represented by different "A" nodes) are known, we do not observe the links between any two firms, leading to the use of matrix reconstruction methods.

[16]In summary, the StatPhys method is a probabilistic method of the entropy method, where for both methods, weights are assigned assuming a proportional allocation of counterparty assets and liabilities among financial firms.

[17]For our results, we assume parameters where firms fully account for changes in the equity of other counterparties that lead to linear market adjustments. The adjustment size is smaller as we include a loss given default of 60% for energy and interbank assets and 40% for short-term assets. The higher loss given default for energy and interbank assets reflects the associated risk of assets with long-term maturities.

Exhibit 6. Total and Average Equity Losses for Energy and Financial Firms by Market



Notes: The exhibit presents bar plots for total (left column) and mean (right column) equity losses for energy firms (top row) and financial firms (middle row) at the market level. The bottom row shows equity losses aggregated by institution. Shaded areas represent initial losses for energy and financial firms, with unshaded areas representing higher-order losses from the network.

Exhibit 6 demonstrates that Indonesian energy firms have the highest total equity losses at $8.19 billion and the highest average losses at $0.30 billion. Compared to Australian firms, total equity losses are 3.7 times higher and average equity losses are 2.2 times higher. Equity losses under the DCF model for Indonesian energy firms stem from the differential in revenues, where coal demand in Thailand and Vietnam decreases for Indonesian exports under the NetZero scenario compared with the BAU scenario. We note that equity losses for energy firms are based only on the decline in revenues from coal production, contributing to losses among financial firms through the CVA's financial firms' performance on energy assets (i.e., direct loans to energy firms).

For financial firms, China incurs the largest projected losses to equity of $9.52 billion, approximately 86% of total equity losses for the countries sampled. Losses are concentrated in Chinese banks; overall, equity losses for banks for the total sample amount to $10.77 billion (see **Exhibit 7**). This constitutes approximately 97% of total equity losses for all financial firms,

Exhibit 7. Total Equity Losses and Mean PD under Transition Scenarios

	Energy Firms						Financial Firms					
Scenarios	**2023**	**2025**	**2028**	**2030**	**2033**	**2035**	**2023**	**2025**	**2028**	**2030**	**2033**	**2035**
Total Equity Losses ($ bn)												
Bel2	7.91	9.81	12.84	14.50	16.32	17.04	7.51	10.56	12.78	13.93	15.14	15.60
Del	4.77	5.73	7.65	9.35	12.26	13.85	4.41	5.36	7.37	9.87	12.27	13.35
Frag	3.18	3.82	5.07	6.19	8.09	9.16	2.91	3.54	4.86	6.15	8.71	9.46
Low	9.17	11.35	14.86	16.75	18.71	19.33	9.06	11.75	14.30	15.59	16.88	17.24
NDCs	3.79	4.51	5.50	5.92	6.23	6.31	3.60	4.43	5.64	6.83	7.04	7.07
NetZero	10.35	12.83	16.54	18.17	19.30	19.37	11.05	12.90	15.46	16.56	17.26	17.24
Mean PD (%)												
Bel2	23.26	28.80	37.79	42.70	48.06	50.27	0.09	0.12	0.15	0.16	0.18	0.18
Del	14.28	16.94	22.28	27.17	35.78	40.60	0.05	0.06	0.09	0.12	0.14	0.16
Frag	9.55	11.32	14.80	18.01	23.66	26.85	0.03	0.04	0.06	0.07	0.10	0.11
Low	26.68	32.95	43.36	48.99	54.91	56.88	0.11	0.14	0.17	0.18	0.20	0.20
NDCs	11.62	13.83	16.92	18.19	19.05	19.26	0.04	0.05	0.07	0.08	0.08	0.08
NetZero	30.15	37.39	48.52	53.44	56.87	57.18	0.13	0.15	0.18	0.20	0.20	0.20

Notes: The exhibit presents total projected equity losses and mean PD for energy and financial firms across different transition scenarios and shock years. We do not display changes from the BAU scenario because this is the assumed trajectory for energy firms (i.e., not a transition shock).

with the remaining 3% of losses accruing to investment banks and investment management firms in our sample.

A large driver of these losses is the volume of energy assets that Chinese financial firms hold. According to the data, energy firms' liabilities are financial firms' assets. Because Chinese banks hold the largest volume of commercial and industrial loans, Chinese banks incur the largest markdown in assets (through CVA) from the equity losses that energy firms incur from the transition scenario. Losses for Chinese banks trigger further market adjustments to the equity of nonbank financial firms in China through short-term asset holdings and of banks in other countries through interbank assets. While nonbanks present a source of risk from the size of their short-term asset holdings, our case study results show that banks are by far the primary source of contagion and should therefore be the focus of financial stability policy and supervision.

As shown in Exhibit 6, financial firms in India exhibit the second-highest projected total equity losses. According to the balance sheet data in Exhibit 4, a large proportion of equity losses for Indian financial firms is driven by counterparty asset holdings, where Indian financial firms hold the second-highest quantity of energy and interbank assets. While this number is lower than in China, these asset holdings are relatively higher than for financial firms in all remaining countries in our study. For example, India is 3 times higher in energy assets and 2 times higher in interbank assets than Vietnam, the third largest market in holding energy and interbank assets. Even with India's high quantity of counterparty asset holdings, average equity losses are smaller in India than in all other countries in our study due to the capital ratios used in the valuation framework, which are second highest in India. A financial firm's capital ratio influences the magnitude of the firm's reevaluation of its assets. For Indian financial firms, a higher capital ratio from the assumed valuation framework leads to a smaller decrease in the value of their counterparty assets.[18]

A significant portion of financial firms' losses comprise initial losses from energy assets. Losses are largest from energy assets because of the first-order impact of the transition scenario. The model shows that higher-order losses are smaller, leading to lower losses from financial firms. Although there are no higher-order impacts from energy firms (because there is no network between energy firms), the direct equity losses lead to a higher devaluation from banks in energy assets, where these institutions hold a large quantity of counterparty assets.

Although losses from counterparty assets between financial firms are smaller than losses from energy assets, they remain sizable. Across all countries in our study (driven mostly by China), more than 40% of total financial firm equity losses stem from interbank and short-term asset holdings (37% for interbank and 7% for short-term asset holdings)—a considerable proportion relative to the 4.5% of financial firms' holdings in these counterparty assets. The contribution

[18]Feedback effects are higher under the entropy method because of the complete interconnectedness of firms holding interbank assets. These shorter pathways enhance the losses incurred by financial firms increasing contagion.

of losses from counterparty asset holdings is relatively high because we account for losses across different financial institutions with counterparty asset holdings. Including other contagion channels, such as fire sales and shareholder equity, would further increase losses incurred by financial firms.

For average equity losses, we find that financial firms in Thailand and Vietnam experience the second- and third-highest average equity losses. For Vietnam, this finding is attributed to the mean capital ratio, where a lower capital ratio leads to a relatively higher devaluation of its asset holdings. For Thailand, if we compare the aggregated balance sheet to that for Malaysia, on average, the assets and equity of financial firms are similar. However, our results show that Thai financial firms, on average, incur the second-highest losses. While the aggregated balance sheet does explain some aspects of equity losses under the transition scenario, a key contribution to equity losses comes from the heterogeneity of financial firms in the network. In the case of Thailand, equity losses are higher on average than in other markets with similar-sized balance sheets. Thus, greater differences among firms in Thailand are factored into the network effect. In contrast, total equity losses for Indian financial firms are the second highest while average equity losses are the smallest. This result is attributable to the mean capital ratio, which is high for India relative to other countries, leading to a lower devaluation of equity than in other markets.

Overall, total equity losses are highest for Chinese financial firms, spilling over to firms in smaller economies. Losses can vary between countries because of the differences in capital ratios, the counterparty exposures firms have, and the heterogeneity of financial firms, which contributes to the network effect.

As part of our wider sensitivity analysis, we consider a range of NGFS transition scenarios for the equity losses and the PD to energy and financial firms. Each of these scenarios is based on different assumptions on projected transition risks that energy firms incur, which will be reflected in the financial firms' losses. We also consider the time the transition scenario is applied, beyond 2023, which affects the extent of the equity losses to energy firms under the DCF model and to financial firms through the network.

Result 2: Under the different transition scenarios we outline, projected total equity losses and mean PD for financial firms increase for a later shock time. Under TRISK, equity losses can deviate by 20% between scenarios, as explored by Baer et al. (2022) and Gasparini, Baer, and Ives (2023). In our results, shown in Exhibit 7, changes in the shock time (i.e., the time of impulse of the given climate transition policy) from 2023 to 2050 can increase equity losses for financial firms by up to 225%; between transition scenarios, equity losses can increase by up to 270%. Similar outcomes are reflected in the mean PD, where for financial firms, the mean PD can increase by up to 184% between scenarios and by up to 230% between shock times. These results show the sensitivity of projected losses to the transition scenario and shock time, highlighting the need to account for these sensitivities when estimating the direct impact on energy firms and the indirect losses to financial firms within the network.

The total equity losses and mean PD are highest for energy and financial firms under the NetZero scenario. The NetZero scenario represents the most stringent case, in which coal production rapidly decreases. Because the shock time in which the transition scenario applies is delayed, we find an increase in equity losses and PD for energy and financial firms. However, the ordering of losses for later shock times is mixed across different scenarios (e.g., before 2033, losses under the Frag scenario are lower than under NDCs and higher in later years). This finding shows that a range of scenarios need to be considered so that losses are not underestimated.

Across all transition scenarios for energy firms, revenue losses representing the difference between the revenue under the BAU scenario and the revenue under the assumed transition scenario are highest in 2050. However, under the assumed time horizon of the DCF model, 2050 represents the period with the highest uncertainty, leading to a higher exponential discounting of revenue and lower contribution to the expected equity losses of energy firms compared to earlier years. Because the DCF applies the highest discounts to changes in cash flows that occur in later years, the size of projected losses decreases in periods when the largest revenue changes are exhibited.

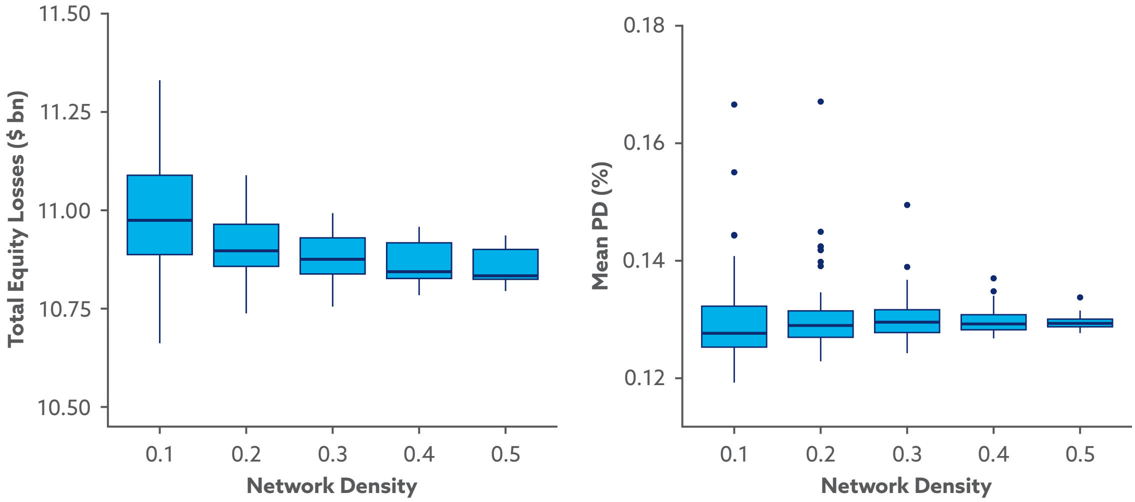
The ordering of equity losses for financial firms corresponds to the equity losses from energy firms because of the network reconstruction method. With this method, changes in the magnitude of losses to energy firms from the different transition scenarios correspond to the same changes in losses for financial firms. The ordering does vary if a sample of networks is generated using the StatPhys reconstruction method, where losses might be higher under a given transition scenario and financial network.

Result 3: Reconstructed networks with fewer interconnections lead to higher equity losses and a higher mean PD for financial firms. We consider losses from changes in the network density for energy, interbank, and short-term assets under the StatPhys method. The network density represents the level of interconnectedness we assume for reconstructed matrices. For example, 100% network density represents a network in which firms are connected to all other firms through counterparty exposures in the network; 0% represents a network with no links. Because we can generate networks under different densities, we consider a sample of networks and compare the range in equity losses, as illustrated by box plots in **Exhibit 8**.[19]

These results are important because they highlight the uncertainty in total equity losses from the network, where the network itself is unobserved. In these unobserved networks, a lower network density can lead to a concentration of losses, where the direct losses to energy firms with high losses under the transition scenario are incurred by fewer financial firms. Depending on the financial firm, there can be either a decrease in the spread of contagion, where

[19]The box plots represent the sample of equity losses at different quartile ranges for each network density. Outliers represent equity losses outside the first and third quartiles, with an additional deviation of 1.5 times the intermediate quartile range (the difference between the first and third quartiles).

Exhibit 8. Total Equity Losses and Mean PD under Different Network Densities



Notes: The exhibit presents box plots for total equity losses (left) and mean PD (right) across a sample of networks generated under the StatPhys matrix reconstruction method for different network densities. Plots are for network densities between 10% and 50% for energy, interbank, and short-term counterparty assets.

financial firms are resilient to equity shocks, or losses that severely affect financial firms that are highly interconnected, resulting in a spread of losses. Both possibilities, particularly in the upper bound of equity losses, should be accounted for in risk management assessments by firms.

For total equity losses, we observe a particular increase in the range of losses for network densities between 10% and 20%. From the contagion channels, the change in losses is concentrated in the energy assets that Chinese financial firms hold from Indonesian coal production firms. A decrease in the network density decreases the diversification effects in the number of energy firms Chinese financial firms are exposed to through energy assets. This leads to a mixed impact wherein equity losses from Chinese financial firms spread to other countries, leading to an increase in the range of total equity losses.

For all network densities, the median total equity losses remain similar, reflecting the consistency of matrix reconstruction methods, where partial information is respected.[20] For the mean PD, we find similar box plots to total equity losses where the range in the PD is higher under lower network densities. Differences exist in the number of outliers observed from a network density of 20%. The increase in the range of losses can be attributed to the PD in a few (outlier) firms, which increases the mean PD under given network structures.

[20]We note that the associated losses from the transition scenario under these lower-density networks are specific to the type of shock considered and the data used. If there is a higher markdown in energy assets under the transition scenario or different types of energy and financial firms are included (e.g., European or US firms), lower-density networks could decrease losses.

Conclusion

The materialization of climate transition risks profoundly affects the financial system, where the risk scale is comparable to that of any economic or financial risk. Losses can be fully assessed only by accounting for the different interdependencies or behaviors associated with financial firms. The state of the financial system is important to regulators and policymakers who shape regulation and to investors who are exposed to these firms. Our study shows the modeling of complex dynamics where losses from the interactions in the system are sizable. We also show that the underlying assumptions driving these results can vary, leading to different implications for the impact of transition risks. Because of the differences in transition scenarios and the connectedness of the financial system, financial firms with exposure to transition risks need to account for high-order losses and the sensitivity of their results. While the sensitivity of results is important in many contexts, such aspects are crucial in climate scenario analysis because of the high uncertainty in the impact and trajectory of climate change. As in this study, tailed risks can be accounted for by setting a range of model parameters, where appropriate risk management provisions can be implemented.

In summary, the key contributions of the paper are as follows:

- **We introduce a network model for financial firms' expected losses to equity under different transition scenarios.** We use the TRISK model to measure the direct equity losses to energy firms under the given transition scenario. We then extend the model using a general network reevaluation model to measure financial firms' losses, where different contagion channels of energy, interbank, and short-term assets are included.
- **Using data for developing countries in Asia and NGFS scenarios, we find that financial firms incur losses directly from energy assets (loans to energy firms), where a sizable proportion of equity losses comes from network contagion (other counterparty asset holdings).** Chinese financial firms (overwhelmingly banks) incur the highest total equity losses because of the size and number of these firms in the data. Financial firms in Thailand and Vietnam incur on average the second- and third-highest equity losses. The results show considerable spillover effects from larger economies to smaller economies, where we account for the network structure, capital ratio, and types of asset holdings on firms' balance sheets. As seen in Exhibit 6, our results show that equity losses from the network between financial firms contributed more than 40% of total equity losses, even though counterparty assets between financial firms are only 4.5% of financial firms' total asset holdings. These results show that indirect losses are sizable and that excluding these dynamics excludes a large source of risk that financial firms are exposed to.

  For the type of financial firms included in our case study, we find aggregate equity losses are highest in total and on average for banks. This result is a consequence of banks' exposure to all contagion channels (i.e., energy assets with energy firms, interbank, and short-term assets with financial counterparties). Although contagion can be sizable for nonbank financial firms in these data, investment banks and investment management firms are not directly exposed to energy firms. Instead, their exposures arise only through interbank and short-term assets with other financial counterparties, including banks. Therefore, banks are overwhelmingly the entity most exposed to transition risks.

- **We find networks of lower density increase projected equity losses and the mean PD.** As the network density decreases, the equity losses that a smaller number of Chinese financial firms are exposed to from Indonesian coal production firms increase. Depending on these firms' balance sheets, these losses are transmitted to other firms, increasing or decreasing total equity losses. Because uncertainty exists in the network—caused by not being able to fully observe all the interconnections—the tailed risks in the upper bound of losses from low-density networks should be accounted for because they could be a large source of contagion for all financial firms in the network.
- Among the different transition scenarios analyzed, overall losses are highest for both energy and financial firms under the NetZero scenario. The NetZero scenario represents the most stringent transition scenario, wherein rapid reductions to coal production volumes and revenues occur. The projected equity losses under NetZero increase significantly the later the policy is implemented. For example, a policy implementation (shock time) in 2035 results in total projected equity losses to financial firms that are more than 1.5 times greater than if the policy were implemented in 2023. Energy and financial firms experience a wide range of losses depending on the shock time and the transition scenario assumed. Firms and policymakers should account for the spectrum of financial firms' losses and the sensitivity of losses to the set of plausible transition pathways.

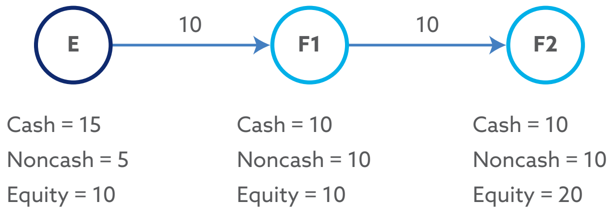
Appendix

We illustrate financial contagion in the extended layer 3 of the TRISK model by providing a small example of how losses are transmitted between firms. Under the network model, we evaluate firms in one equilibrium position in which all firms can meet their obligations. We then assess the change in equity under another equilibrium that accounts for losses under the transition scenario. The movement from an equilibrium position is initiated by an initial shock, represented by the transition scenario, where continuous reevaluations occur to account for the losses of impacted firms until a new equilibrium position is reached. The following example is illustrative only and does not represent the size of adjustments observed in the data.

Example: The network methodologies used are part of a large body of literature on financial network contagion as explored by Eisenberg and Noe (2001), Rogers and Veraart (2012), Furfine (2003), and Battiston, Puliga, Kaushik, Tasca, and Caldarelli (2012). We focus mainly on the general network reevaluation methodology, which can include frameworks from other papers. This approach has been used in other stress testing and financial stability works (Roncoroni, Battiston, D'Errico, Halaj, and Kok 2021). The conceptual framework of the model is as follows:

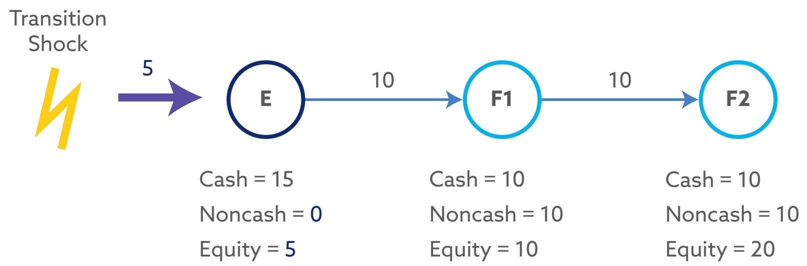
1. We have a network of energy (red node) and financial (blue node) firms (see **Exhibit A1**). A stylized balance sheet is displayed underneath each node where firms hold cash, noncash (representing energy firms' physical assets and financial firms' counterparty assets from the inward direction of arrows), liabilities (directed outward arrows), and equity. Assets (cash and noncash) must equal liabilities plus equity. From the setup, all firms can meet their liabilities through their asset holdings, representing an equilibrium position.

Exhibit A1. First Equilibrium Position of a Small Financial Network Example



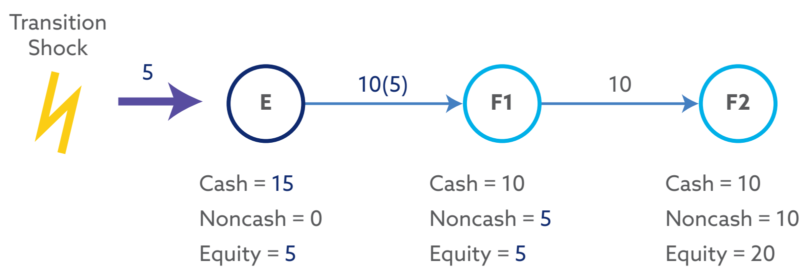
2. Assume as in **Exhibit A2** that a transition scenario leads to a loss of 5 for the energy firm (where losses under the TRISK model are generated by changes in the revenue of physical [production] assets under the DCF model), resulting in a decrease in its book value of equity. Losses are absorbed by the energy firm's noncash holdings, thereby decreasing its equity by 5.

Exhibit A2. Direct Losses to Firm E under the Transition Scenario



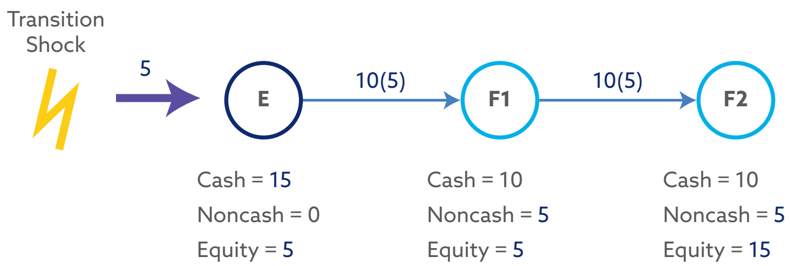
3. F1 holds a counterparty asset from the energy firm (i.e., a loan from F1 to E) and performs a CVA markdown of the asset value (see **Exhibit A3**). This occurs as F1 accounts for the decrease in the creditworthiness of E, where F1 assumes that the impaired revenue generation of E means that it will be less likely to meet its financial obligations to F1. The firm marks down the asset by 50% to account for a linear decrease in the equity of the energy firm by 50% (represented by the value above the arrow). In this regard, the counterparty liabilities of the energy firm remain unchanged, whereas the value has decreased from counterparty assets the financial firm holds. The counterparty losses incurred by F1 decrease its equity from 10 to 5.

Exhibit A3. Counterparty Losses to Firm F1 under Reevaluation from Firm E



4. F2 decreases the value of its associated counterparty asset from F1 because of the decrease in F1's book value of equity, similarly decreasing its noncash holdings and equity by 5 (see **Exhibit A4**). Until reevaluation, all firms can meet their liabilities through their asset holdings, representing a new equilibrium position for the financial system.

Exhibit A4. Counterparty Losses to Firm F2 under Reevaluation from Firm F1



References

Baer, M., B. Caldecott, J. Kastl, A. M. Kleinnijenhuis, and N. Ranger. 2022. "TRISK – A Climate Stress Test for Transition Risk" (20 October). Available at SSRN: https://ssrn.com/abstract=4254114.

Barucca, P., M. Bardoscia, F. Caccioli, M. D'Errico, G. Visentin, G. Caldarelli, and S. Battiston. 2020. "Network Valuation in Financial Systems." *Mathematical Finance* 30 (4): 1181–204. doi:10.1111/mafi.12272.

Battiston, S., A. Mandel, I. Monasterolo, and A. Roncoroni. 2023. "Climate Credit Risk and Corporate Valuation." Available at SSRN: https://ssrn.com/abstract=4124002.

Battiston, S., M. Puliga, R. Kaushik, P. Tasca, and G. Caldarelli. 2012. "DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk." *Scientific Reports* 2 (1): 1–6. doi:10.1038/srep00541.

Bolton, P., M. Despres, L. A. Pereira da Silva, F. Samama, and R. Svartzman. 2020. *The Green Swan: Central Banking and Financial Stability in the Age of Climate Change*. Bank for International Settlements (BIS).

Carney, M. 2015. "Breaking the Tragedy of the Horizon: Climate Change and Financial Stability." Speech given at Lloyd's of London (19 September). www.bankofengland.co.uk/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability.

Cimini, G., T. Squartini, D. Garlaschelli, and A. Gabriella. 2015. "Systemic Risk Analysis on Reconstructed Economic and Financial Networks." *Scientific Reports* 5 (article number 15758). doi:10.1038/srep15758.

Cormack, C., C. Donovan, A. Koberle, and A. Ostrovnaya. 2020. "Estimating Financial Risks from the Energy Transition: Potential Impacts from Decarbonization in the European Power Sector." *Journal of Energy Markets* 13 (4). https://www.risk.net/journal-of-energy-markets/volume-13-number-4-december-2020.

Eisenberg, L., and T. H. Noe. 2001. "Systemic Risk in Financial Systems." *Management Science* 47 (2): 236–49. doi:10.1287/mnsc.47.2.236.9835.

Elderson, F. 2023. "'Come Hell or High Water': Addressing the Risks of Climate and Environment-Related Litigation for the Banking Sector." Speech given at European Central Bank Legal Conference, Frankfurt, Germany (4 September). www.ecb.europa.eu/press/key/date/2023/html/ecb.sp230904_1~9d14ab8648.en.html.

Furfine, C. H. 2003. "Interbank Exposures: Quantifying the Risk of Contagion." *Journal of Money, Credit, and Banking* 35 (1):111–28. doi:10.1353/mcb.2003.0004.

Gasparini, M., M. Baer, and M. Ives. 2023. "A Re-evaluation of the Financial Risks of the Net Zero Transition." Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4254054.

Global Carbon Project. 2023. "Global Carbon Budget 2023." Earth System Science Data (ESSD). https://essd.copernicus.org/articles/15/5301/2023/.

Haldane, A. G., and R. M. May. 2011. "Systemic Risk in Banking Ecosystems." *Nature* 469 (7330): 351–55. doi:10.1038/nature09659.

IEA. 2022. "Southeast Asia Energy Outlook 2022." https://iea.blob.core.windows.net/assets/e5d9b7ff-559b-4dc3-8faa-42381f80ce2e/SoutheastAsiaEnergyOutlook2022.pdf.

IEA and IFC. 2023. "Scaling Up Private Finance for Clean Energy in Emerging and Developing Economies." https://iea.blob.core.windows.net/assets/a48fd497-d479-4d21-8d76-10619ce0a982/ScalingupPrivateFinanceforCleanEnergyinEmergingandDevelopingEconomies.pdf.

IMF. 2023. "Global Financial Stability Report: Financial and Climate Policies for a High-Interest-Rate Era" (October). www.imf.org/-/media/Files/Publications/GFSR/2023/October/English/text.ashx.

Jung, H., R. F. Engle, and R. Berner. 2021. "CRISK: Measuring the Climate Risk Exposure of the Financial System." Federal Reserve Bank of New York Staff Reports, no. 977. https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr977.pdf.

Koundouri, P., M. A. Chatzigiannakou, K. Dellis, C. Landis, G. Papayiannis, and A. Yannakopoulos. 2024. "Integrated Assessment Models: Classification and Synthesis." In *UN SDSN Global Climate Hub Report: Modelling Net Zero Pathways*. https://unsdsn.globalclimatehub.org/wp-content/uploads/2024/02/COP28_subreport_IAMs.pdf.

NGFS. 2023. "NGFS Climate Scenarios Technical Documentation, V4.2" (November). https://www.ngfs.net/sites/default/files/media/2024/01/16/ngfs_scenarios_technical_documentation_phase_iv_2023.pdf.

Nguyen, Q., I. Diaz-Rainey, D. Kuruppuarachchi, M. McCarten, and E. K. M. Tan. 2023. "Climate Transition Risk in U.S. Loan Portfolios: Are All Banks the Same?" *International Review of Financial Analysis* 85:102401. doi:10.1016/j.irfa.2022.102401.

Pang, R., and G. Shrimali. 2024. “Financial Network Valuation under Climate Transition Risk” (25 July). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4905653.

RMI. 2022. “2° Investing Initiative Transfers Stewardship of PACTA to RMI.” Press release (8 June). https://rmi.org/press-release/2-degree-investing-initiative-transfers-stewardship/.

Rogers, L. C. G., and L. A. M. Veraart. 2012. “Failure and Rescue in an Interbank Network.” *Management Science* 59 (4): 882–98. doi:10.1287/mnsc.1120.1569.

Roncoroni, A., S. Battiston, M. D’Errico, G. Halaj, and C. Kok. 2021. “Interconnected Banks and Systemically Important Exposures.” *Journal of Economic Dynamics & Control* 133:104266. doi:10.1016/j.jedc.2021.104266.

Upper, C. 2011. “Simulation Methods to Assess the Danger of Contagion in Interbank Markets.” *Journal of Financial Stability* 7 (3): 111–25. doi:10.1016/j.jfs.2010.12.001.

Veraart, L. A. M. 2020. “Distress and Default Contagion in Financial Networks.” *Mathematical Finance* 30 (3): 705–737. doi:10.1111/mafi.12247.

Authors

Raymond Pang
Senior Affiliate Researcher, CFA Institute

Gireesh Shrimali
Head of Transition Finance Research, Oxford Sustainable Finance Group
and UK Centre for Greening Finance & Investment

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